Evaluating Open-ended Text Generation of Large Language Models using Spectral Distances of Surprisal

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Abstract

We propose a novel automatic evaluation metric for open-ended text generation, which is a substantial improvement of the recently developed method, Fourier analysis of cross-entropy (FACE), hence, FACE-2. FACE-2 is a psycholinguistically inspired metric that extracts the dynamic patterns (spectrum) of text surprisal. Examined with open-ended text generation tasks, FACE-2 significantly outperforms a broad set of baseline metrics in revealing the model scaling effect, which scales up to models of 70B parameters, while many other existing metrics fail to capture this effect. We have also confirmed the advantage of FACE-2 in producing stronger agreement with human preferences from a large human-annotated dataset. We advocate for including metrics that mine the dynamics of likelihood in evaluating open-ended text generation, which covers broader aspects of human language than only using static likelihood-based or semantic-based metrics.

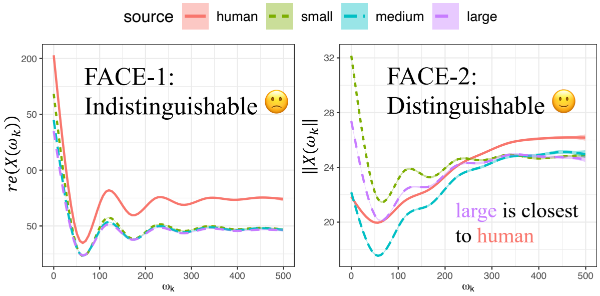

Figure 1: An example showing improvement of FACE-2 (this study) over FACE-1 in better distinguishing texts generated by models of different sizes. "small"⇒1.5b, "medium"⇒7b, "large"⇒72b, all from Qwen2 family. Curves are spectra of surprisal fit with GAM.

1 Introduction

The surprisal (likelihood) of texts is an important source of information for evaluating the outcome of natural language generation tasks, especially for open-ended generation. Ever since the early works that directly use surprisal for evaluation, such as GLTR (Gehrmann et al., 2019), Solaiman et al. (2019), and Ippolito et al. (2020), more sophisticated methods have been recently developed to further harness the potentials of surprisal: some utilize the curvature of surprisal (e.g., DetectGPT and Fast-Detect) Mitchell et al. (2023); Bao et al. (2024), and some rely on its variance (e.g., GPT-who) (Venkatraman et al., 2024). These works have achieved impressive effect in telling apart model-generated texts from those "authentic" human-written ones.

A less-taken way is to use the *dynamic* property of surprisal, that is, how surprisal changes over time (or, the position in body of text), as the basis for evaluation. This idea has roots in psycholinguistics theories about how the cognitive effort for processing natural language is constrained temporally, such as the uniform information density (UID) (Florian Jaeger, 2010) and entropy rate constancy (ERC) (Genzel and Charniak, 2002) theories. As far as we are aware of, Fourier analysis of cross-entropy (FACE) (Yang et al., 2023) is the first attempt in this direction, and FourierGPT (Xu et al., 2024) adopts its method for the generated text detection task.

However, while focusing on the task of evaluating open-ended text generation, we found that evaluation metrics have not kept pace with the development of Large Language Models (LLMs). Metrics like FACE and MAUVE (Pillutla et al., 2021) have been tested mainly on older, smaller models (such as GPT-2 and OPT). In the current landscape, with the emergence of larger and newer models (like Llama3 (Touvron et al., 2023) and Qwen2 (qwe, 2024)), their conclusions may no longer hold. Indeed our experimental results show that many historically popular metrics fail to evaluate current models correctly, while FACE still demonstrates a degree of effectiveness.

To better align with the evaluation of open-ended text generation for modern LLMs, we introduce **FACE-2**, an improved version of the original FACE metric (referred as **FACE-1** throughout the study). Our major improvements are: (i) including optimized processing steps of surprisal which is the basis for NLG evaluation; (ii) implementing several new distance functions on spectrum representations which are mathematically more sound. We conclude our contribution as follows:

1. We rethink the limits of an existing open-ended text generation metric FACE-1, and introduce an upgraded metric, namely FACE-2.
2. We conducted experiments using some modern and more recent LLMs (e.g., Llama3 and Qwen2) and scaled up the experiment size to 70B.
3. Our experiments on the evaluation of LLM capacity and alignment with human preference show that most metrics from the past cannot correctly evaluate modern LLMs, while spectrum-based metrics still maintain some effectiveness.
4. Our analysis shows that FACE-2 is much more reliable than FACE-1, and the spectrum-based metric still has the potential to grow.

2 Related Work

2.1 Surprisal Studies in Psycholinguistics and the Related NLG Evaluation Metrics

Since our proposed metric FACE-2 is based on surprisal, here we introduce the concept by reviewing the related linguistic studies as well as the NLG evaluation framework based on that.

Surprisal is a well studied concept in psycholinguistics, which has been known to reflect the cognitive processes underlying human language usage, with evidence a wealth of corpus-based and behavioral studies (Jaeger and Levy, 2006; Smith and Levy, 2013). The most relevant previous empirical findings for FACE-1 and this study are about temporal property of surprisal, i.e., how surprisal changes over time. The earlist work to the best of our knowledge, dates back to Genzel and Charniak (2002) and also discussed in Dethlefs et al. (2016), who find that human users to dialogue systems are sensitive to the *peaks* and *troughs* of entropy in speech. Xu and Reitter (2016) take a closer look at the sub-structure of spontaneous dialogues, and find that the utterance surprisal from two speakers converge towards each other within topical segments. Further, Xu and Reitter (2017) hypothesize that the observed convergence of surprisal can be attributed to the innate *periodicity* of language processing capacity limited by human cognitive load during communication, and back it up with evidence that the spectral features of surprisal are useful predictors for success in task-oriented dialogues. Similar investigations are carried out on free conversations (Maës et al., 2022), task-oriented dialogues in written and spoken modalities (Giulianelli et al., 2021), and larger datasets (Giulianelli and Fernández, 2021).

Based on the previous empirical studies on the surprisal, word (token) level surprisal has been widely used for evaluating the quality of generated text. Gehrmann et al. (2019) used heatmap-like method to directly visualize the difference in token surprisal between GPT2-generated and human written text, where high-surprisal tokens are visualized with warmer colors, i.e., the red end on spectrum, while low-surprisal tokens with colder colors.

Entering the era of large language models, the surprisal view of language started to gain more attention from researchers who are interested in developing more effective and cognitive-inspired evaluation tools for natural language generation. An example is FACE-1 (Yang et al., 2023), which adopts the spectral method in Xu and Reitter (2017) to the evaluation of open-ended text generation. Follow-up works started using the fluctuation of surprisal as an indicator of whether the text was generated by model or human writers, leading to several successful psycholinguistics-inspired text detection methods, such as GPT-who (Venkatraman et al., 2024) and FourierGPT (Xu et al., 2024). Among these studies, FourierGPT's method is most related to our study.

While FACE-1 has previously obtained a success in the evaluation of open-ended text generation, it still has some limitations:First, FACE-1 is mathematically flawed and its choice for distance functions lacks careful curation (see Section 3). Secondly, it is developed and tested using GPT-2 (Radford et al., 2019) generated data, and thus the original conclusions on modeling scaling effects and sampling methods does not necessarily apply to current LLMs.

2.2 Limitations of Existing NLG Evaluation Metrics

Besides the NLG evaluation metrics based on surprisal, a broad set of other metrics can also be used for evaluating open-ended text generation: **Self-**

BLEU, a lexical overlap-based metric proposed by Zhu et al. (2018) and based on BLEU (Papineni et al., 2002); **Zipf** score, proposed by Holtzman et al. (2020) (see Section 2.1); **MAUVE**, a metric based on the similarity between quantized semantic representations of texts (Pillutla et al., 2021); **BERTScore**, a semantic similarity-based metric using pretrained BERT models (Zhang et al., 2020); **BARTScore**, a generation-based metric that uses the log-likelihood of generation (from source to target) to measure text quality (Yuan et al., 2021).

However, all of the above-listed metrics are developed in the pre-ChatGPT era, at which point advanced techniques like data engineering, training engineering, and scaling laws had not yet fully investigated. It means that many of the current conclusions about these metrics' performances might be out-of-date. Therefore, we need a new comprehensive study to update our understanding of their effectiveness on more recent LLMs.

3 FACE-2 Workflow

The general workflow of FACE-2, as described in Figure 2, can be summarized in the following steps:

Step 1 - Estimate surprisal Given $\mathcal{D}$ as text set, we use an language model evaluator to calculate the surprisal of each sentence in $\mathcal{D}$. For a sentence of N tokens $t_1, \ldots, t_N$, its surprisal sequence $\mathcal{S} = s_1, \ldots, s_{N-1}$ is defined as $s_i \triangleq -\log p(t_i|t_1, \ldots, t_{i-1})$, i.e., the negative log-probability for each token estimated by the language model. There $|\mathcal{D}|$ pieces of such surprisal sequences produced at this step.

Inspired by FourierGPT (Xu et al., 2024), we additionally apply a z-score normalization to the spectrum to improve the numerical stability of the spectrum value. The surprisal sequence becomes:

$$\begin{aligned} \tilde{s}(n) &= \frac{s(n) - \mu}{\sigma} \\ \text{where } \mu &= \sum s(n)/N, \\ \sigma &= \sum (s(n) - \mu)^2/(N-1) \end{aligned} \tag{1}$$

Step 2 - Fourier transform We treat $\mathcal{S}$ as a signal in time domain, and apply the discrete Fourier transform (defined in Cooley and Tukey, 1965):

$$X(\omega_k) \triangleq \sum_{n=0}^{N-1} \tilde{s}(n) e^{-j\omega_k n} \tag{2}$$

Note that here we change the index subscript from i to n to avoid confusion with the imaginary unit i, which is denoted by j instead ($j^2 = -1$). Thus $s(n)$ is equivalent to s_i. The obtained series of complex numbers $\mathcal{F} = \{X(\omega_k)\}$ is the spectral representation of the original surprisal signal in frequency domain, where $\omega_k = \frac{2\pi k}{N}$ is the k-th frequency component, $k = 0, \ldots, N-1$.

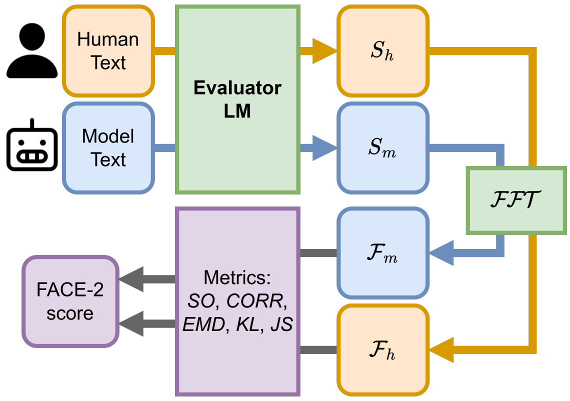

Figure 2: The basic workflow of the FACE-2 approach.

Step 3 - Spectrum preprocessing The mathematical definition of FACE-1 is flawed because it takes only $real(X(\omega_k))$ as the spectrum, ignoring the information carried by the imaginary component. As a fix, in FACE-2 we use L2-norms $\|X(\omega_k)\| = \sqrt{real(X(\omega_k))^2 + imag(X(\omega_k))^2}$ as the final spectrum representation.

Step 4 - Measure similarity of spectrum Given text data from two sources, $\mathcal{D}_h$ (human written) and $\mathcal{D}_m$ (model generated), and their spectra $\mathcal{F}_h$ and $\mathcal{F}_m$ obtained from previous stages, respectively. By our assumption, the quality of generated text can be reflected in its distance from human text in spectral space, that is, some distance/similarity measures between $\mathcal{F}_m$ and $\mathcal{F}_h$. FACE-1 uses four similarity functions: Spectral overlap (SO), Pearson's correlation (CORR), cosine distance, and Spearman's correlation (SPEAR), where CORR and cosine distance are mathematically equivalent, and SPEAR performs poorly.

Therefore, in this study we remove the duplicate and poor-performed metric proved in FACE-1 study, and then propose to use three new distance functions: Earth Mover's Distance (EMD) (Rubner et al., 1998), Kullback-Leibler divergence (KL)(Kullback and Leibler, 1951), and Jenson-Shannon divergence (JS, also named total divergence to the average by Dagan et al., 1997). These functions are chosen because they are widely used for measuring the distance between probability dis-

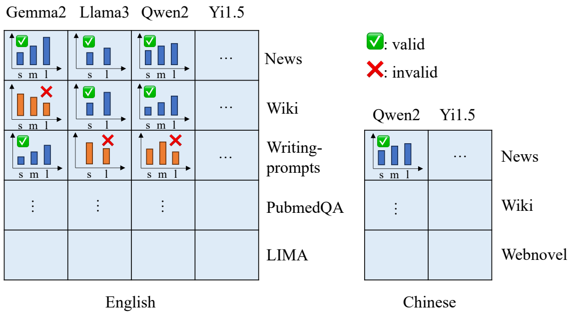

Figure 3: Illustration of how the scaling effect of generator models is analyzed. The tables represent generator model × task combinations. The "s", "m", "l" indicate small, medium, and large model size, respectively.

tributions, and all come with good interpretability.

In particular, EMD is a long-standing distance function suitable for image retrieval with spectral features (Rubner et al., 2000; Deborah et al., 2015), which motivates us to migrate it to a similar scenario, that is, text similarity comparison based on spectral features (both image data and language data are treated as time series). KL is an asymmetric for measuring the difference between two distributions, which is suitable here because a normalized spectrum can be considered as a distribution. JS is a symmetrized and smoothed version of KL, and it is adopted to mitigate the asymmetricality issue in KL.

In sum, five metrics are adopted in FACE-2, SO, CORR, EMD, KL and JS, defined as:

$$\text{SO} = \text{AUC}(\mathcal{F}_h \cap \mathcal{F}_m)/\text{AUC}(\mathcal{F}_h \cup \mathcal{F}_m) \tag{3}$$

$$\text{CORR} = cov(\mathcal{F}_h, \mathcal{F}_m)/\sigma(\mathcal{F}_h)\sigma(\mathcal{F}_m) \tag{4}$$

$$\text{EMD} = \int_{-\infty}^{\infty} |\mathcal{F}_h - \mathcal{F}_m| \tag{5}$$

$$\text{KL} = \sum_{x \in [0,\pi/2]} \mathcal{F}_h(x)\ \log(\frac{\mathcal{F}_h(x)}{\mathcal{F}_m(x)}) \tag{6}$$

$$\text{JS} = \frac{1}{2}\text{KL}(\mathcal{F}_h, \mathcal{F}_{h+m}) + \frac{1}{2}\text{KL}(\mathcal{F}_m, \mathcal{F}_{h+m}) \tag{7}$$

In these formulas, $\mathcal{F}_h$ and $\mathcal{F}_m$ are the text spectra from human and models, respectively, and $\mathcal{F}_{h+m} = \frac{1}{2}(\mathcal{F}_h + \mathcal{F}_m)$. The AUC in Equation (3) refers to the area under the curve. According to EMD's definition in Equation (5), it reflects the amount of "work" must be done to transform one distribution $\mathcal{F}_m$ into another $\mathcal{F}_h$. In KL and JS, the spectrum is first normalized into a probability distribution.

4 Experiments

In order to bring the evaluation of open-ended text generation in line with the current development of LLM, we evaluate **FACE-2**, our main objective of experiments, a simple baseline metric, **surprisal**, which directly uses the log-likelihood of the evaluator model, and **all other metrics mentioned in section 2.2** in our extensive large-scale experiments. Our experiment would include some widely used LLMs range from 0.5B to 70B, and test these metrics' agreement with model size and human preference. We evaluate the performance of FACE-2 compared other metrics, with respect to the following two desiderata:

1. **Model scaling effect**: How well do the metric scores align with the scaling effect of model size, that is, larger models are better than smaller ones.[1] (Section 4.2)
2. **Agreement with human preferences**: How well do the metric scores align with human preference for text quality. (Section 4.3)

The open-ended text generation can be described as: given a sequence as the prompt, the goal is to generate the full text (or response, for instructed model) based on the prompt.Hyperparameters such as sampling strategies, maximum and minimum generation lengths, and GPU hour costs are reported in Appendix A.4.

4.1 Datasets and models

Datasets The prompts for generation are from eight datasets in two languages (English and Chinese). The majority of data are in **written** modality: *Wiki*, *News*, and *Story*, which are common choices in previous studies (Pillutla et al., 2021; Mitchell et al., 2023; Bao et al., 2024). For English, we include two extra datasets in **dialogue** modality for an extended investigation. The three Chinese datasets are Wikipedia dump (Wikimedia-Foundation), MNBVC-News (MNBVC Team, 2023), and WebNovel (Jun, 2023). The five English datasets are Wikipedia dump (Wikimedia-Foundation), BBC-News (RealTimeData), and WritingPrompts (Fan et al., 2018), PubmedQA (Jin et al., 2019), a domain-specific dataset, and LIMA (Zhou et al., 2023) a general QA dataset.

[1]We would make a brief explanation of the scaling effects. It is a conclusion derived from Arena leaderboard (Chiang et al., 2024), where all LLMs are compared and rated by human preference with ELO ranking. Amount the same model family, a larger model always ranks higher.

The generation tasks in written modality are assigned to base models, and the dialogue modality is for instruction-tuned models. Detailed statistics and data cleaning steps are reported in Appendix A.2 and Table 3.

Models The models used for text generation are: LLaMA-3 (8b, 70b) (Touvron et al., 2023) and Gemma-2 (2b, 9b, 27b) (Team, 2024) for English generation only, and Qwen-2 (1.5b, 7b, 72b) (Yang et al., 2024) and Yi-1.5 (6b, 34b) (Young et al., 2024) for both English and Chinese generation. The metrics will be evaluated on these generated texts. FACE-2 requires an evaluator to calculate the surprisal as described in Section 3, we use Pythia (410m, 1.4b) (Biderman et al., 2023) and LLaMA3 (8b, 70b) as evaluator for English, and Qwen-2 (0.5b, 1.5b, 7b, 72b) as evaluator for both English and Chinese. We did not use English model for Chinese experiments, since they are not well trained on Chinese datasets, which makes them tend to behave in English pattern.

We compare performances of different model families in various sizes, with details reported in Table 4 in Appendix A.3.

4.2 Result: Model scaling effect

We test the degree to which "scaling law" holds to the metric scores of generated texts, by *counting* the number of cases that strictly satisfy the condition large $\succ$ medium $\succ$ small, in terms of generator size, where the $\succ$ operator means that its left operand scores better than its right operand, which is defined differently across metrics.

We consider all model family $\times$ task combinations as shown in Figure 3: the English table consists of 4 (column: generator models) $\times$ 5 (row: tasks) $=$ 20 combinations; the Chinese table consists of $2 \times 3 = 6$ combinations, accordingly. A cell of the table contains the evaluation scores for the texts generated from three versions of the same model: *small*, *medium*, and *large* (except Llama3, which only has two versions). For each cell, if the scores strictly satisfy the inequality *large* $\succ$ *medium* $\succ$ *small*, we put a valid mark. Otherwise, we mark that cell invalid. Finally, we use the *ratio of valid cells* to indicate the degree to which a specific metric follows the scaling law.

This analysis is based on the belief that larger models should demonstrate better overall generation performance, including the open-ended text generation task, which is a reasonable inference from the scaling laws of LLMs (Raffel et al., 2020; Kaplan et al., 2020; Brown, 2020). Under this belief, a good metric that claims to characterize the model's capability of generating "high-quality" texts should be able to produce scores that rank larger models higher than smaller ones. That means we can judge the soundness of a metric by calculating the valid cell ratio as the basis for comparison. For example, if metric m_A results in 7 out of 20 valid cells for English, which out-performs the 5 out of 20 from another metric m_B, then we can conclude that both are better than a random guess ($1/P_3^3 = 1/6 \approx 0.167$), but m_A is preferred over m_B as the former shows stronger scaling effect.

We first compare FACE-2 with its predecessor FACE-1 and the naive surprisal method. As shown in Table 1, **FACE-2 has higher ratios than FACE-1 and surprisal**, and all metrics surpass the random guess baseline. The numbers in Table 1 are means and SDs from the 4 evaluators for each language, and thus the advantage of FACE-2 is stable and significant. The best performing distance function is EMD for English, and JS for Chinese.

Then in Table 2 we compare the best performance (among all evaluators) of FACE-2 with those metrics that do not depend on multiple evaluator models. FACE-2 using EMD as the distance function has the highest ratio in English data, and FACE-2 using CORR wins in Chinese. In sum, from the two tables, we can conclude that FACE-2 can better reflect the scaling effect of model size than its predecessor and most existing metrics, in open-ended text generation tasks. For a more intuitive presentation, we illustrate GAM-smoothed spectrum curves from multiple generator model sizes, examining whether larger models are closer to human (see Figure 4), in which FACE-2 curves indeed better resemble human spectrum.

Besides the main conclusion, we also conduct ablation studies on the z-score normalization, the L2-norm on spectrum, and the selection of distance functions, which are discussed as follows.

Ablation on z-score z-score normalization on surprisal before applying Fourier transform has mostly positive effect on the outcomes: the highest ratios in Table 1 come from z-scored rows; z-score operation is particularly helpful to the ensemble cases in Chinese (the meaning of ensemble will be explained later); the English ensemble cases are odd. This result sheds new light to our understanding of surprisal in language: the "relative" values

Lang.	Metric	Valid Cell Ratio
English	FACE-1$_{\text{SO}}$	0.356 (0.053)
	FACE-2$_{\text{EMD}}$ (L2)	0.388 (0.088)†
	FACE-2$_{\text{EMD}}$ (z + L2)	**0.400 (0.173)**
	FACE-2$_{\text{Ensemble-3}}$ (L2)	0.331 (0.070)
	FACE-2$_{\text{Ensemble-3}}$ (z + L2)	0.194 (0.042)
	FACE-2$_{\text{Ensemble-5}}$ (L2)	0.281 (0.065)
	FACE-2$_{\text{Ensemble-5}}$ (z + L2)	0.175 (0.046)
	surprisal	0.363 (0.143)
Chinese	FACE-1$_{\text{SO}}$	0.417 (0.083)
	FACE-2$_{\text{SO}}$ (L2)	0.417 (0.319)
	FACE-2$_{\text{JS}}$ (z + L2)	**0.583 (0.083)**
	FACE-2$_{\text{Ensemble-3}}$ (L2)	0.292 (0.083)
	FACE-2$_{\text{Ensemble-3}}$ (z + L2)	0.542 (0.160)†
	FACE-2$_{\text{Ensemble-5}}$ (L2)	0.292 (0.083)
	FACE-2$_{\text{Ensemble-5}}$ (z + L2)	0.500 (0.136)
	surprisal	0.375 (0.415)
	random guess	$1/6 \approx 0.167$

Table 1: FACE-2 compared to FACE-1 and surprisal in the valid cell ratio that satisfies the assumption of "large $\succ$ medium $\succ$ small" in terms of generator size. Numbers in parentheses are standard deviations. Subscript of FACE indicates the distance function used, or an ensemble method. z stands for applying z-score normalization on the surprisal. L2 stands for extracting L2-norm from the spectrum. Best scores for each language group are in bold, and † indicates the second best.

Lang.	Metric	Valid Cell Ratio
English	FACE-2$_{\text{EMD}}$	**0.600**
	FACE-2$_{\text{Ensemble-3}}$	0.450†
	FACE-2$_{\text{Ensemble-5}}$	0.400
	MAUVE	0.200
	Zipf	0.350
	Self-BLEU	0.150
	BERTScore	0.450†
	BARTScore	0.000
Chinese	FACE-2$_{\text{CORR}}$	**0.833**
	FACE-2$_{\text{EMD}}$	0.667†
	FACE-2$_{\text{Ensemble-3}}$	0.667†
	FACE-2$_{\text{Ensemble-5}}$	0.667†
	MAUVE	0.333
	Zipf	0.333
	Self-BLEU	0.000
	BERTScore	0.667†
	BARTScore	0.167
	random guess	$1/6 \approx 0.167$

Table 2: The valid cell ratios resulted from FACE-2 (best among all evaluators) and other metrics. Best scores are in bold, and † indicates the second best.

are more important than absolute ones in describing the dynamic patterns of how surprisal changes in text. In other words, the spectral features of surprisal are evaluator-independent ones, possibly reflecting some robust cognitive-load-related features of the generated (or human-written) texts.

Ablation on L2-norm The effect of L2-norm on spectrum is not as salient. While the highest ratio in Table 1 is achieved in the L2-normed FACE-2, the overall ratios across all distance functions, however, is almost equally good in FACE-1 (see Table 8 in Appendix B.3). This is counter-intuitive as L2-norm harnesses more spectral information than only using the real part, and it also contradicts the findings in FourierGPT (Xu et al., 2024). We think this might be due to the noisy frequency leakage problem in raw Fourier analysis, which could be mitigated by adding smoothing windows to surprisal. We leave it to future work.

Selection of distance functions In general, the new distance functions in FACE-2 lead to higher valid cell ratios. For instance in Table 1, EMD $>$ SO for English and JS $>$ SO for Chinese. For practical use, we investigate whether an **ensemble** method that aggregates multiple distance functions can still produce satisfying results. When comparing text A and B, the ensemble method is to cast majority vote among the judgements from multiple distance functions. For example, if 3 out of 5 agree A is better than B, then it will be the ensemble result. We experiment with **Ensemble-3**, which votes among EMD, KL and JS (the three new ones), and **Ensemble-5**, which includes all five distance functions. We find that Ensemble-3 produces slightly better results. It is a complex task to determine which distance function to use, and given the current results, EMD and Ensemble-3 are the best options for most cases.

Problem of surprisal as a metric We notice that using pure surprisal as a metric also reaches decent ratios: 0.363 for English and 0.375 for Chinese, which are close to those of FACE-1. However, these ratios have much larger standard deviations, which are due to the usage of different evaluators: It indicates an apparent problem of using raw surprisal to evaluate text generation: surprisal scores are low (preferred) when the evaluator matches in model size with the generator; otherwise, surprisal scores are high (unwanted). Therefore, using pure surprisal as a metric is extremely biased towards the evaluator used, and consequently, cannot produce consistent evaluation scores that meets the common intuition that "larger model is better".

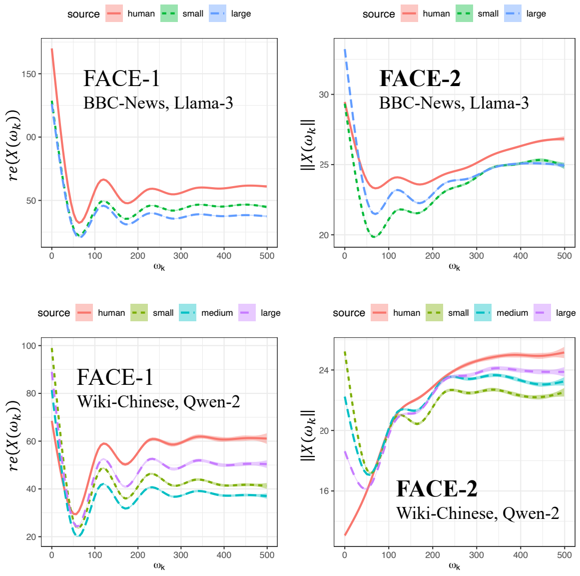

Figure 4: Exemplars of GAM smoothed spectrum plots. The spectra from FACE-2 are on the right column, FACE-1 on the left. FACE-2 can reveal the expected order: larger models produce spectrum (blue and purple) that resembles human (red) more.

Comparison with other metrics Amount all the other metrics, BERTScore is the only metric that obtains the second-best performance. To our surprise, the MAUVE ratios are pretty low: 0.200 for English and 0.333 for Chinese. It seems that the texts generated by models of various sizes (at least within the investigation scope of this study) cannot be effectively distinguished using semantic representations, such as the clustering-based method by MAUVE. Zipf achieves comparable ratios as surprisal, but its computational cost is expensive. The lowest ratios are Self-BLEU and BARTScore, both of which did not even perform better than random guess.

Comparison with sampling methods We compare the FACE-2 score between different sampling methods in Appendix B.1, the results show that a better sampling method (e.g., top-p with p=0.95 and top-k with k=40) would have a better FACE-2 score.

4.3 Result: Agreement with human preferences

Preference Dataset in MT-Bench FACE-1 and MAUVE experiments used a human preference dataset to evaluate their metric's agreement with human preference (Pillutla et al., 2021)[2], generated by GPT-2. To keep the evaluation up-to-date, we use the human annotation dataset in MT-Bench (Zheng et al., 2023)[3] instead. It is a larger and more recent dataset, containing texts generated by six models: GPT-4, GPT-3.5-turbo, Claude-v1, LlaMA-13B, Alpaca-13B, Vicuna-13B, and also pairwise comparison results of these texts given by human judges.

Preference Ranking The way of MT-Bench calculating its ranking is that: Given texts that are presented in pairs to crowd-sourced human judges, $\langle T_A, T_B \rangle$, where T_A is generated by model A and T_B by model B, the judges are requested to answer whether A or B wins, or if it is a tie (See Appendix C in Zheng et al. (2023)). Then the Bradley-Terry algorithm (Bradley and Terry, 1952) is used to convert the winning records of all models to a ranked list of scores (called BT scores); therefore, we obtain a ranked list based on human preference: $S_A > S_B > \cdots > S_F$. It represents the models' relative performances according to the human judges': model A better than model B and so on.

Similarly, we replace human judges with scoring results for each pair of texts given by a metric, so that we obtain a ranked list based on the given metric: $S'_B > S'_F > \cdots > S'_A$. The alignment between these two rank lists can be measured by Pearson's correlation; it tells how well the metric agrees with human preferences.

GPT-4 as the Approximation of Human The "sloppiness" in MT-Bench is that it does not contain human-written texts as groundtruth, which is required by pairwise comparison-based metrics, such as FACE-2. To deal with this, we use GPT-4's responses (the model that closest to human) as the approximated human ground-truth, thereby excluding GPT-4 in our final ranking list. Therefore, the workflow of FACE-2 within this experiment is that: first compute the FACE-2 scores using the approximated human groundtruth, then conduct pairwise comparison between each texts, and finally get the ranking list by computing BT-Score.

Agreement with Human Preferences The BT-scores from FACE-2, FACE-1, and the other five metrics are plotted in Figure 5 in comparison with

[2]Available here: https://github.com/krishnap25/mauve-experiments.

[3]https://huggingface.co/datasets/lmsys/mt_bench_human_judgments

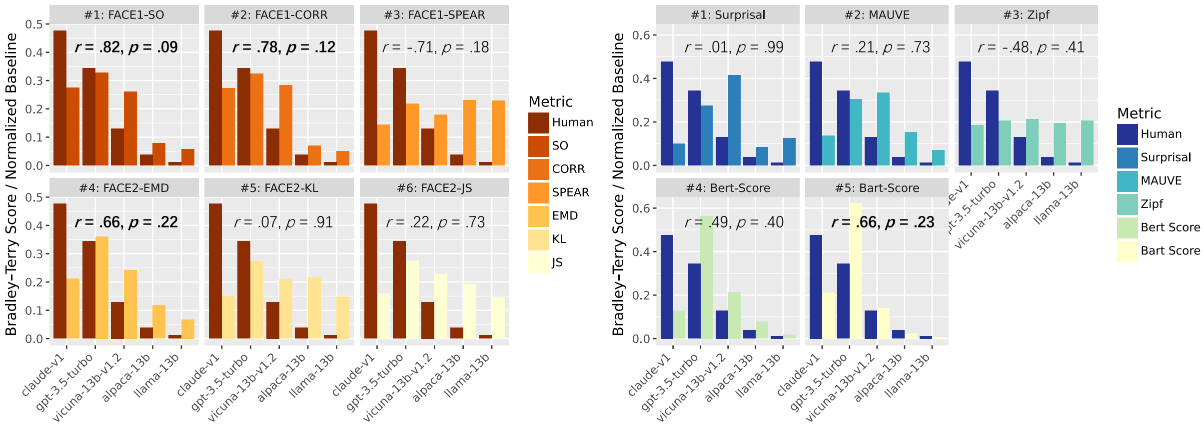

Figure 5: Bradley-Terry scores that reflect human preferences and evaluation metrics over model generated texts. A higher bar indicates the corresponding source of text is more preferred by human (dark color) or metrics (lighter colors). FACE score generally have higher correlations with human preferences.

those from human preferences. From the correlation scores, we can see that both **FACE-1 and FACE-2 have stronger agreement with human preferences than other metrics**. This indicates that spectrum-based methods are robust in different datasets. Among the 3 new metrics, EMD performs as well as SO and CORR, while KL and JS not. We argue that it is because the text length of MT-Bench dataset is relatively short, which makes the spectral distances more able to be disrupted by noise. Except for BARTScore, all other metrics perform poorly in agreement with human preference. It indicates that most of their conclusions on human agreements have failed today. The results consolidate the thought behind FACE: the human perception of text is better characterized by temporal changes of surprisal, other than raw surprisal or semantic features.

In our further case analysis, we found that the biggest disagreement between human preferences and metrics was caused by Claude-v1, which causes low correlation scores in all cases. Appendix B.5 may shed some light on it.

5 Discussion and Conclusion

In this study, we address the issue that most of the metrics designed for open-ended text generation are published in the era where LLMs are not fully developed, therefore it is necessary to rethink their effectiveness in evaluating current LLMs. Spectrum-based methods exhibit high potential; therefore, we proposed an improved version of Fourier Analysis of Cross-Entropy, FACE-2, a metric set to evaluate open-ended text generation in the current LLM era.We also carried out large-scale experiments within up to 70B LLMs to update the effectiveness conclusions of many old evaluation metrics in the current LLM era. Our results show that most of the old conclusions have failed, whereas spectrum-based methods maintain its effectiveness to a certain degree. We observed the outperformance of FACE-2 in experiments of model scaling effects, and the effectiveness and robustness of both spectrum-based methods in experiments of agreement with human preferences.

When compared with its predecessor and other metrics, FACE-2 demonstrates the following advantages: Firstly, it can more effectively distinguish texts generated by models of various sizes, i.e., better reflecting the scaling effect. This is observed across various model families and languages, which, more impressively, is achieved without depending on large evaluating models. Secondly, with the newly introduced metrics (EMD, KL, and JS) and the new z-score normalization step, it outperforms FACE-1 and a broad set of baseline metrics. Thirdly, the advantage of FACE in agreement with human preferences are confirmed in a larger dataset.

In sum, the new evaluation method for open-ended text generation, FACE-2, is effective, robust, and computationally efficient. It reaches state-of-the-art performance. However, no metric can fully capture the complex nature of human languages. As LLMs keep evolving, the gap between generated and real content will keep shrink. We believe that seeking metrics to magnify this gap is a meaningful response to the eternal question of where the boundary between AI and human is.

6 Limitations

There are still limits in the current study. Firstly, larger models 100b+ parameters and commercial models, such as GPT-4, are not included, whose experiments are needed for further validation of FACE-2's capability. Secondly, the majority of the generator models examined are base-models but not chat-models, although we believe that the foundational generation capabilities are determined at pre-training stage and is sufficient for current experiments, ideally, more experiments with chat-models for needed comprehensive evaluations, because chat-models are the most common use cases of LLMs. However, it is currently challenging to find public dialogue data with human ground-truth that can be directly used for generation tasks, especially for Chinese data and other languages. Thirdly, how to select the optimal distance function for FACE-2 is yet to be determined. Our current results indicate EMD, JS, and CORR are most promising, and a simple ensemble method (Table 2) seems working, it still requires a systematic investigation. Lastly, it is not clear why the spectrum of surprisal provides information can reflect the sources of generator models. We need further evidence that map the spectral features in "frequency domain" to the observable linguistic patterns in "time domain", for example, sentence structure, lexical or syntactical choices and so on. We will try to address these limitations in the future work, and further improve FACE to a more interpretable method.

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A Appendix: Reproduction

A.1 Other metrics

We compare FACE-2 with FACE-1, and other four metrics:

Surprisal It is straight-forward: the lower surprisal a text produces according to an evaluator, the better score it receives. The exponentiated average surprisal of a sequence of words is exactly how perplexity is defined.

MAUVE It returns a number in the scope of $[0, 1]$. A larger value indicates a more similar semantic distribution to human written texts, which indicates higher text quality. The score is computed using the public implementation provided by Pillutla et al. (2021).

Zipf It is the slope of the best-fit line on log-log plot of a rank versus unigram frequency plot. A smaller value indicates it is closer to human distributions, i.e., higher text quality. We use the open-sourced implementation from Holtzman et al. (2020).

Self-BLEU This score is computed by following the same protocol of Holtzman et al. (2020): computing the BLEU score of each generations against all other generations as references. A lower final score suggests higher diversity of the generated text, which is an important indicator of text quality.

A.2 Data and cleaning steps

The mapping between domains and specific datasets are listed in Table 3.

Language	Domain	Dataset
Chinese	Wiki	Wikipedia-Chinese
	News	MNBVC-News
	Story	WebNovel
English	Wiki	Wikipedia-English
	News	BBC-News
	Story	WritingPrompts
	Domain QA	PubmedQA
	General QA	LIMA

Table 3: Both Chinese datasets and English datasets contain continuous writing tasks of three domains: News article, Wikipedia document, and Story. Additionally, we provide two open-ended text generation datasets for instructed models.

Model Cat.	Family	Size	Lang.
Generator	Qwen-2	1.5b, 7b, 72b	Chinese
	Yi-1.5	6b, 34b	
	Llama-3	8b, 70b	English
	Gemma-2	2b, 9b, 27b	
Evaluator	Qwen-2	0.5b, 1.5b, 7b, 72b	Chinese
	Pythia	410m, 1.4b	English
	Llama-3	8b, 70b	

Table 4: Models used in the experiment. For English datasets, both Chinese models and English models are used for generation and evaluation experiments. For Chinese datasets, we uses Chinese generators only, and Qwen-2 for Chinese evaluation.

We clean the datasets to ensure quality: repetitions of sentence or meaningless strings are removed; next we sample a subset from each dataset, ensuring the texts in the subsets as controlled variable have comparatively equal length. For all datasets from the three main categories (except for WritingPrompts), we split each into two parts, with the first half as the prompt for generation, and the second half as human ground-truth. The prompt length is set to 64 tokens, and during generation, we limit the model maximum generation length to 1024. For two QA datasets plus WritingPrompts, we directly use the prompt provide by themselves. The size of each subset we used are 5000, except for Wikipedia-Chinese and MNBVC-News, where we removes some texts containing too much English. The size of Wikipedia-Chinese's subset is 2160, and MNBVC-News' is 4206. LIMA originally contains 1030 groups of dialogue, we remove those excessively long dialogue, the size of remaining subset is 900.

To further ensure consistency in generation, we use the same tokenizer across all generator models. For Chinese, we use the default tokenizer from Qwen2, and for English it is the Llama3 tokenizer.

A.3 Model details

Detailed sizes of the generator and evaluator models are listed in Table 4.

A.4 GPU usage and hyper-parameters

We used 4 A6000ada 48G GPU for the experiments in this studies. We used vllm to speed up generation and inference. We notice that vllm does not guarantee stable log probability, but this instability only affects the vocabularies' log probabilities in

Sampling Method	SO ↑	EMD(×100)↓	KL(×10) ↓	JS(×10) ↓
Greedy	0.55	6.43	2.64	2.40
Pure Sampling	0.57	1.77	1.92	2.12
Top-k (k=40)	0.57	1.72	1.90	2.11
Top-k (k=640)	0.57	1.76	1.92	2.12
Nucleus (p=0.95)	0.58	1.72	1.91	2.11

Table 5: FACE-2 score. Tested on Gen: Gemma2-2b-base, Inf: Llama3-70b-base, Data: BBC. (×n) means the metric value multiplied by n.

decimal places (≤1e-3), which can be ignored.

The arguments for the sampling method in text generation are as follows:

- `temperature`: 1
- `top k`: 50
- `top p`: 0.95

The estimated times for running generator and evaluator models is listed in Table 6. To deal with an out-of-memory bug in vllm, we clear the cuda cache after each step of output. This slows down the speed about 20%∼30%. Taking all model family × task combinations together, the total running time of our experiments is about $(20 + 6) \times 3\text{h} \approx 140\text{h}$.

Task	Model Size	Running Time
Generation	1.5b	10min∼20min
	7b	20min∼30min
	30b (4×GPUs)	1h∼2h
	70b (4×GPUs)	1h∼2h
Evaluation	0.5b	5min
	1.5b	5min
	7b	10min
	70b (4×GPUs)	40min∼2h

Table 6: Runtime of generation tasks and evaluation tasks for different model sizes. The runtime we reported is a rough value, which may vary according to the environment.

B Appendix: Results

B.1 Sampling methods

We further make some comparison on the use of different sampling methods in Table 5. The results in the table generally suggest that a better sampling method (p=0.95 and k=40) have better FACE-2 scores - the same conclusion as FACE-1.

B.2 Spectrum plots

The full spectrum plots of all model family × task combinations are shown in Figure 5.

B.3 Full valid cell ratios

The full results of valid cell ratios are shown in Table 8.

B.4 MT-Bench comparison

The detailed MT-Bench comparison results are reported in Table 9. We exclude GPT-4 and re-compute the results of original MT-Bench human preference BT-score. We also report the BT-score of FACE-2 metrics EMD and SO, and FACE-1 SO. We see that the old metric SO performs only slightly difference in scores, while the new metric EMD is much closer to human BT-score than SO. Since MAUVE is not capable for pair-wise comparison, we report the raw MAUVE score over these five models directly.

B.5 Case analysis for the mismatch in Claude-v1 output

The mismatch between human preference and metric scores in Claude-v1 outputs might be due to the fact that Claude-v1 is more likely to perform as a chat model and outputs explanations while others directly write what is requested. For example, we notice that, when the prompt is "*Compose an engaging travel blog post about a recent trip to Hawaii, highlighting cultural experiences and must-see attractions.*", Claude-v1 first generates a sentence like "*Here is a draft travel blog post about a recent trip to Hawaii:*", and then gives the main body of post. In contrast, other models tend to generate the post directly. Evaluation metrics are sensitive to this kind of semantic changes, while human participants of MT-Bench that are uninformed of model-generated texts' features focus more on the content quality. Hence FACE considers that

Claude-v1's text is far from natural, while humans rank its content to the top.

B.6 Case study of how FACE works better than BERTScore

We use an example from LIMA to demonstrate the situation that FACE-2 works better than BERTScore. The three models are Qwen 1.5b, 7b, and 72b. Comparing their outputs, we found that the larger model gives the better answer that close to LIMA's groundtruth. The 1.5b model outputs a large amount of useless codes and texts. The 7b model gives suggestions by showing codes, which might solve the problem, but clearly not a general solution we hoping to see. The 72b model successfully gives a general solution, which includes a key information **ScaleType** also mentioned by the groundtruth answer. FACE-2 scores can successfully evaluate these models, but BERTScore considers 7b model outperforms 72b (see Table 7).

Model	BERTScore↑	FACE-2_{SO}↑	FACE-2_{EMD}↓	FACE-2_{JS}↓
Qwen 1.5b	85.30	57.53	2.41	20.83
Qwen 7b	88.29	60.78	1.27	20.14
Qwen 72b	87.85	65.57	0.82	18.81

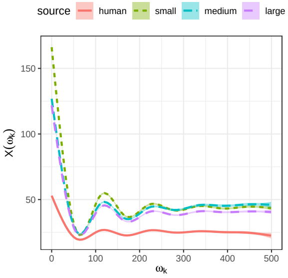
Table 7: BERTScore evaluates the model size wrong, while all FACE-2 metrics evaluate it right.

Metric	Lang.	z-score	Dist. func.	Evaluator								Mean (SD)
				en1	en2	en3	en4	zh1	zh2	zh3	zh4	
FACE-1 (real part)	en	no	SO	0.30	0.25	0.40	0.40	0.40	0.35	0.40	0.35	0.36(0.05)
			CORR	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30(0.00)
			EMD	0.40	0.30	0.45	0.40	0.45	0.40	0.30	0.40	**0.39(0.05)**
			KL	0.35	0.50	0.35	0.40	0.35	0.30	0.35	0.55	0.39(0.08)
			JS	0.35	0.50	0.40	0.40	0.35	0.30	0.35	0.45	0.39(0.06)
		yes	SO	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.45	0.36(0.03)
			CORR	0.25	0.50	0.20	0.20	0.10	0.05	0.15	0.55	0.25(0.17)
			EMD	0.25	0.10	0.55	0.50	0.60	0.55	0.30	0.35	**0.40(0.17)**
			KL	0.20	0.35	0.20	0.20	0.25	0.20	0.15	0.30	0.23(0.06)
			JS	0.25	0.35	0.20	0.20	0.20	0.15	0.25	0.30	0.24(0.06)
	zh	no	SO	-	-	-	-	0.50	0.50	0.33	0.33	0.42(0.08)
			CORR	-	-	-	-	0.33	0.33	0.33	0.33	0.33(0.00)
			EMD	-	-	-	-	0.67	0.50	0.50	0.67	**0.58(0.08)**
			KL	-	-	-	-	0.50	0.50	0.50	0.50	0.50(0.00)
			JS	-	-	-	-	0.33	0.50	0.50	0.67	0.50(0.12)
		yes	SO	-	-	-	-	0.50	0.50	0.67	0.67	**0.58(0.08)**
			CORR	-	-	-	-	0.17	0.00	0.33	0.83	0.33(0.31)
			EMD	-	-	-	-	0.50	0.67	0.50	0.50	0.54(0.07)
			KL	-	-	-	-	0.67	0.33	0.50	0.50	0.50(0.12)
			JS	-	-	-	-	0.50	0.33	0.50	0.50	0.46(0.07)
FACE-2 (L2-norm)	en	no	SO	0.40	0.45	0.35	0.25	0.40	0.40	0.30	0.40	0.37(0.06)
			CORR	0.15	0.15	0.20	0.40	0.05	0.00	0.00	0.45	0.18(0.16)
			EMD	0.40	0.45	0.35	0.25	0.40	0.55	0.35	0.35	**0.39(0.08)**
			KL	0.35	0.35	0.25	0.35	0.30	0.35	0.45	0.45	0.36(0.06)
			JS	0.15	0.25	0.30	0.35	0.30	0.25	0.35	0.50	0.31(0.09)
		yes	SO	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35(0.00)
			CORR	0.10	0.15	0.25	0.50	0.05	0.05	0.10	0.50	0.21(0.18)
			EMD	0.50	0.50	0.30	0.10	0.60	0.60	0.40	0.20	**0.40(0.17)**
			KL	0.25	0.20	0.10	0.20	0.15	0.15	0.10	0.10	0.16(0.05)
			JS	0.20	0.25	0.20	0.30	0.20	0.20	0.15	0.25	0.22(0.04)
	zh	no	SO	-	-	-	-	0.67	0.67	0.33	0.00	**0.42(0.28)**
			CORR	-	-	-	-	0.00	0.00	0.17	0.50	0.17(0.20)
			EMD	-	-	-	-	0.33	0.17	0.17	0.50	0.29(0.14)
			KL	-	-	-	-	0.33	0.33	0.33	0.33	0.33(0.00)
			JS	-	-	-	-	0.33	0.50	0.17	0.33	0.33(0.12)
		yes	SO	-	-	-	-	0.50	0.50	0.50	0.50	0.50(0.00)
			CORR	-	-	-	-	0.17	0.00	0.17	0.83	0.29(0.32)
			EMD	-	-	-	-	0.67	0.67	0.50	0.17	0.50(0.20)
			KL	-	-	-	-	0.67	0.50	0.33	0.33	0.46(0.14)
			JS	-	-	-	-	0.67	0.67	0.50	0.50	**0.58(0.08)**

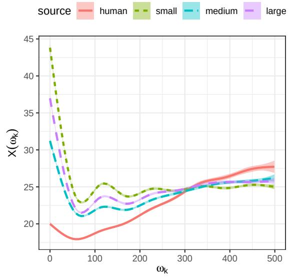
Table 8: The full valid cell ratios from all experiments. Best results from each trial are highlighted. The English evaluator models (en1-en4) are pythia-410m, pythia-1.4b, llama3-8b, and llama3-70b. The Chinese evaluator models (zh1-zh4) are qwen2-0.5b, qwen2-1.5b, qwen2-7b, and qwen2-72b, respectively.

Human-BT		MAUVE		FACE2-SO-BT		FACE2-EMD-BT		FACE1-SO-BT	
Model	Score	Model	Score	Model	Score	Model	Score	Model	Score
Claude-v1	0.476	Vicuna-13b	0.708	GPT3.5-turbo	0.333	GPT3.5-turbo	0.303	GPT3.5-turbo	0.344
GPT3.5-turbo	0.342	GPT3.5-turbo	0.644	Vicuna-13b	0.242	Claude-v1	0.273	Vicuna-13b	0.281
Vicuna-13b	0.130	Alpaca-13b	0.325	Claude-v1	0.182	Vicuda-13b	0.212	Claude-v1	0.188
Alpaca-13b	0.039	Claude-v1	0.287	Alpaca-13b	0.152	Alpaca-13b	0.121	Alpaca-13b	0.125
Llama-13b	0.012	Llama-13b	0.149	Llama-13b	0.091	Llama-13b	0.091	Llama-13b	0.063

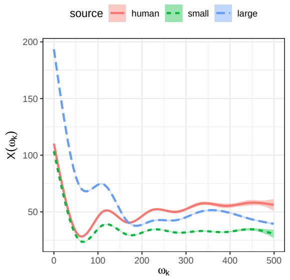
Table 9: Detailed MT-Bench comparison between human preference, FACE, and MAUVE.



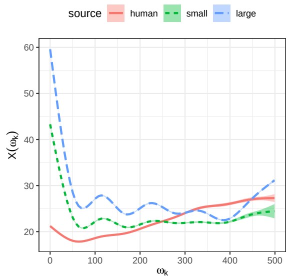
FACE-1 Lima Qwen-2



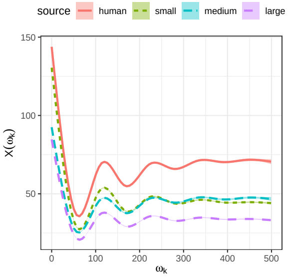
FACE-2 Lima Qwen-2



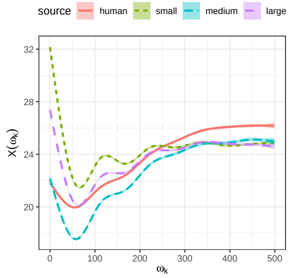
FACE-1 Lima Llama-3



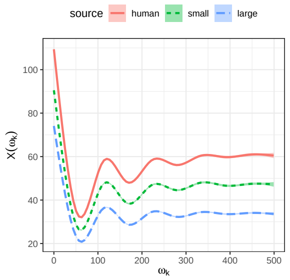
FACE-2 Lima Llama-3



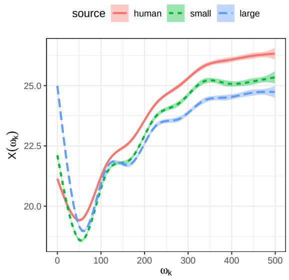
FACE-1 Wiki-EN Qwen-2



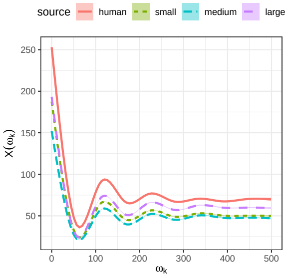
FACE-2 Wiki-EN Qwen-2



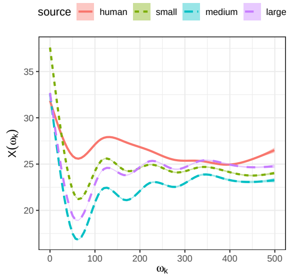
FACE-1 Wiki-EN Llama-3



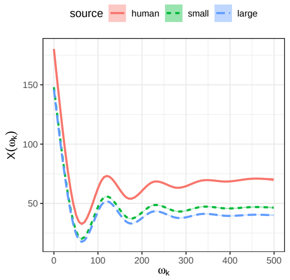
FACE-2 Wiki-EN Llama-3



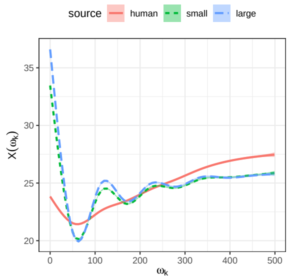
FACE-1 WebNovel Qwen-2



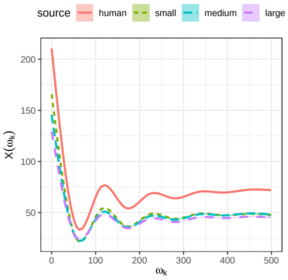
FACE-2 WebNovel Qwen-2



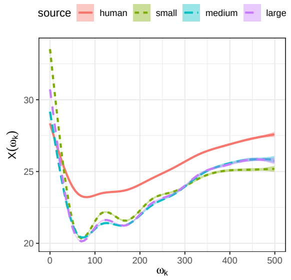
FACE-1 WP Llama-3



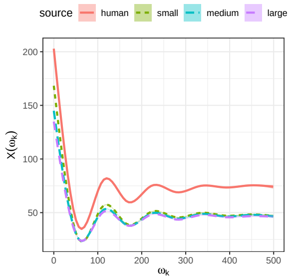
FACE-2 WP Llama-3



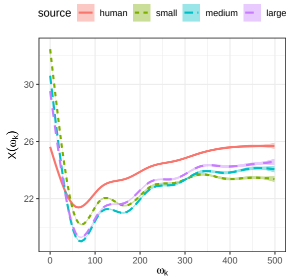
FACE-1 BBC-News Qwen-2



FACE-2 BBC-News Qwen-2



FACE-1 ZH-News Qwen-2



FACE-2 ZH-News Qwen-2

Figure 6: Other spectrum plots demonstrating FACE-2 generally reflect model scaling effect better than FACE-1.

Input

In Android, I defined an “‘ImageView“‘’s “‘layout_width“‘ to be “‘fill_parent“‘ (which takes up the full width of the phone).
If the image I put to “‘ImageView“‘ is bigger than the “‘layout_width“‘, Android will scale it, right? But what about the height? When Android scales the image, will it keep the aspect ratio?
What I find out is that there is some white space at the top and bottom of the “‘ImageView“‘ when Android scales an image which is bigger than the “‘ImageView“‘. Is that true? If yes, how can I eliminate that white space?

Groundtruth

* Yes, by default Android will scale your image down to fit the ImageView, maintaining the aspect ratio. However, make sure you're setting the image to the ImageView using "'android:src="...""' rather than "'android:background="...""'. "'src="' makes it scale the image maintaining aspect ratio, but "'background="' makes it scale and distort the image to make it fit exactly to the size of the ImageView. (You can use a background and a source at the same time though, which can be useful for things like displaying a frame around the main image, using just one ImageView.)
* You should also see "'android:adjustViewBounds"' to make the ImageView resize itself to fit the rescaled image. For example, if you have a rectangular image in what would normally be a square ImageView, adjustViewBounds=true will make it resize the ImageView to be rectangular as well. This then affects how other Views are laid out around the ImageView.
Then as Samuh wrote, you can change the way it default scales images using the "'android:scaleType"' parameter.
By the way, the easiest way to discover how this works would simply have been to experiment a bit yourself! Just remember to look at the layouts in the emulator itself (or an actual phone) as the preview in Eclipse is usually wrong.

Qwen2-1.5b Output

I need to make the whole image stay in the "'ImageView"' and not take the whole screen, but not scale it at the same time.

```
<RelativeLayout xmlns:android="http://schemas.android.com/apk/
    res/android"
     xmlns:tools="http://schemas.android.com/tools"
     android:id="@+id/layout_root"
     android:layout_width="fill_parent"
     android:layout_height="fill_parent"
     android:orientation="vertical"
     tools:context=".MainActivity">
     <ImageView
          android:id="@+id/imageView1"
          android:layout_width="fill_parent"
          android:layout_height="fill_parent"
          android:src="@drawable/background"/>
</RelativeLayout>
```

The problem is that the image is scaled so it covers up the space in the layout.

```
<RelativeLayout xmlns:android="http://schemas.android.com/apk/
    res/android"
     xmlns:tools="http://schemas.android.com/tools"
     android:id="@+id/layout_root"
     android:layout_width="fill_parent"
     android:layout_height="fill_parent"
     android:orientation="vertical"
     tools:context=".MainActivity">
     <ImageView
          android:id="@+id/imageView1"
          android:layout_width="fill_parent"
          android:layout_height="fill_parent"
          android:src="@drawable/background" />
     <ImageView
          android:id="@+id/imageView2"
          android:layout_width="fill_parent"
          android:layout_height="fill_parent"
          android:src="@drawable/background"/>
</RelativeLayout>
```

... a lot of unnecessary text and code ...

Qwen2-7b Output

And more interestingly, in iOS, when I put an image that is bigger than the layout width, there will be no white space at all. Is that true?
If I understand the question correctly:
When you do ‘ImageView‘’s ‘LayoutParams.width = LayoutParams.MATCH_PARENT;‘ and the image width is larger than your ‘Layout‘ size (screen size), Android will resize it (stretch it) to fit the ‘Layout‘.
But if you try to set ‘LayoutParams.height = LayoutParams.MATCH_PARENT;‘, it will set ‘LayoutParams.height‘ to ‘ImageView‘ to 0, because ‘LayoutParams.height‘ is a ‘int‘ instead of a ‘layout_constraintDimension‘ like ‘LayoutParams.width‘. So in this case, Android won’t scale the image to keep the ratio or not. You have to control ‘LayoutParams.height‘ by layout constraints.
By setting ‘android:adjustViewBounds="true"‘ in ‘ImageView‘’s attribute, Android will stretch images to fill the area, respecting its original aspect ratio. It won’t add extra white space. Here is an example:

```
<ImageView
    android:id="@+id/imageView"
    android:layout_width="match_parent"
    android:layout_height="match_parent"
    android:src="@drawable/some_image"
    android:adjustViewBounds="true"/>
```

Regarding iOS, yes, it has the same behavior. When iOS scales the image and its width exceeds the view’s width, it will stretch it to the width of the view, while maintaining the original aspect ratio. It won’t add any white space above or below the image. And there is no need to set the layout size to MATCH_PARENT, as by default it will take all available space. However, it is possible that you still see white space if you are manually setting any other constraints or attributes that affect the image’s dimensions. In iOS, you can also use the Auto Layout feature to set constraints for your ‘UIImageView‘ to avoid any white spaces. The key points are:
- Set ‘UIImageView’s contentMode‘ to ‘.scaleAspectFit‘. It adjusts the view to the given layout bounds while keeping the aspect ratio. - Set ‘ImageView’s constraints‘ to fill the parent view in both width and height. - Set the necessary auto layout constraints to position the ‘UIImageView‘.
In both environments, you don’t have to worry about white spaces if you properly set up the constraints and attributes related to the image scaling and positioning. Hope this helps! If you need more details or examples, let me know. I’m happy to provide further assistance.

Qwen2-72b Output

You could set android:scaleType="centerCrop" on your ImageView. This will ensure that your image will be shown in the largest size possible in your space and maintain aspect ratio.
Your options are:
“‘ ImageView.ScaleType.CENTER: Scale the image to fit inside the ImageView’s bounds, centering it. Aspect ratio is maintained.
ImageView.ScaleType.CENTER_CROP: Scale the image to fit inside the ImageView’s bounds, centering it and cropping to fit. Useful for images that are not the same aspect ratio as the ImageView.
ImageView.ScaleType.CENTER_INSIDE: Scale the image so that it fits entirely inside the ImageView. Aspect ratio is maintained, and the image will not be scaled down if its smaller than the ImageView.
ImageView.ScaleType.FIT_CENTER: Scale the image to fit inside the ImageView, centering and using the image’s top and left as a center point. This scale type is like CENTER but ensures that the entire image will be visible.
ImageView.ScaleType.FIT_END: Scale the image to fit inside the ImageView, aligning the image’s right and bottom to the right and bottom of the ImageView. This scale type is like FIT_START but the alignment is at the end of the ImageView.
ImageView.ScaleType.FIT_START: Scale the image to fit inside the ImageView, aligning the image’s top and left to the top and left of the ImageView.
ImageView.ScaleType.FIT_XY: Scale the image to fit the ImageView’s bounds. The image may be stretched to fit in this space.
ImageView.ScaleType.MATRIX: Uses a supplied Matrix object to scale and position the image. The image will be clipped by the ImageView if it extends outside the ImageView bounds.
“‘
See [the documentation](http://developer.android.com/reference/android/widget/ImageView.ScaleType.html) for a description of each one.